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(54) **PRESCRIPTIVE ANALYTICS BASED MULTI-TIER ELASTIC-POOL DATABASE REQUISITION STACK FOR CLOUD COMPUTING**

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G06F 16/21 (2019.01)
G06N 20/00 (2019.01)
G06F 16/28 (2019.01)

(52) **U.S. Cl.**

CPC ***G06F 16/217*** (2019.01); ***G06F 16/282*** (2019.01); ***G06N 20/00*** (2019.01)

(58) **Field of Classification Search**

CPC .. G06F 16/217; G06F 16/282; G06F 11/3433; G06F 2201/80; G06F 11/3409; G06F 11/3452; G06N 20/00

See application file for complete search history.

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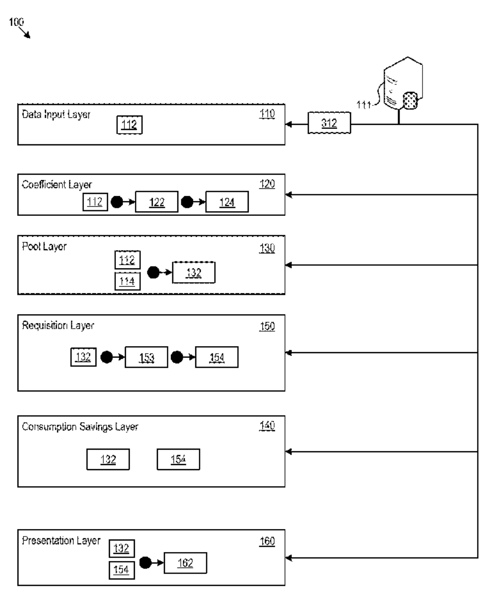
(57) **ABSTRACT**

A multi-layer elastic requisition stack may generate pool requisition tokens for controlling requisition of pooled database-compute resources. The elastic requisition stack may determine candidate databases for inclusion in elastic pools by analyzing historical utilization data and generating predicted utilization data. Based on the historical and predicted utilization data, the elastic requisition stack may determine multiplexing characteristics for the candidate databases and complement factors among the databases. The elastic requisition stack may compare unpooled database performance to pooled database performance to determine whether to pool the candidate databases.

20 Claims, 6 Drawing Sheets



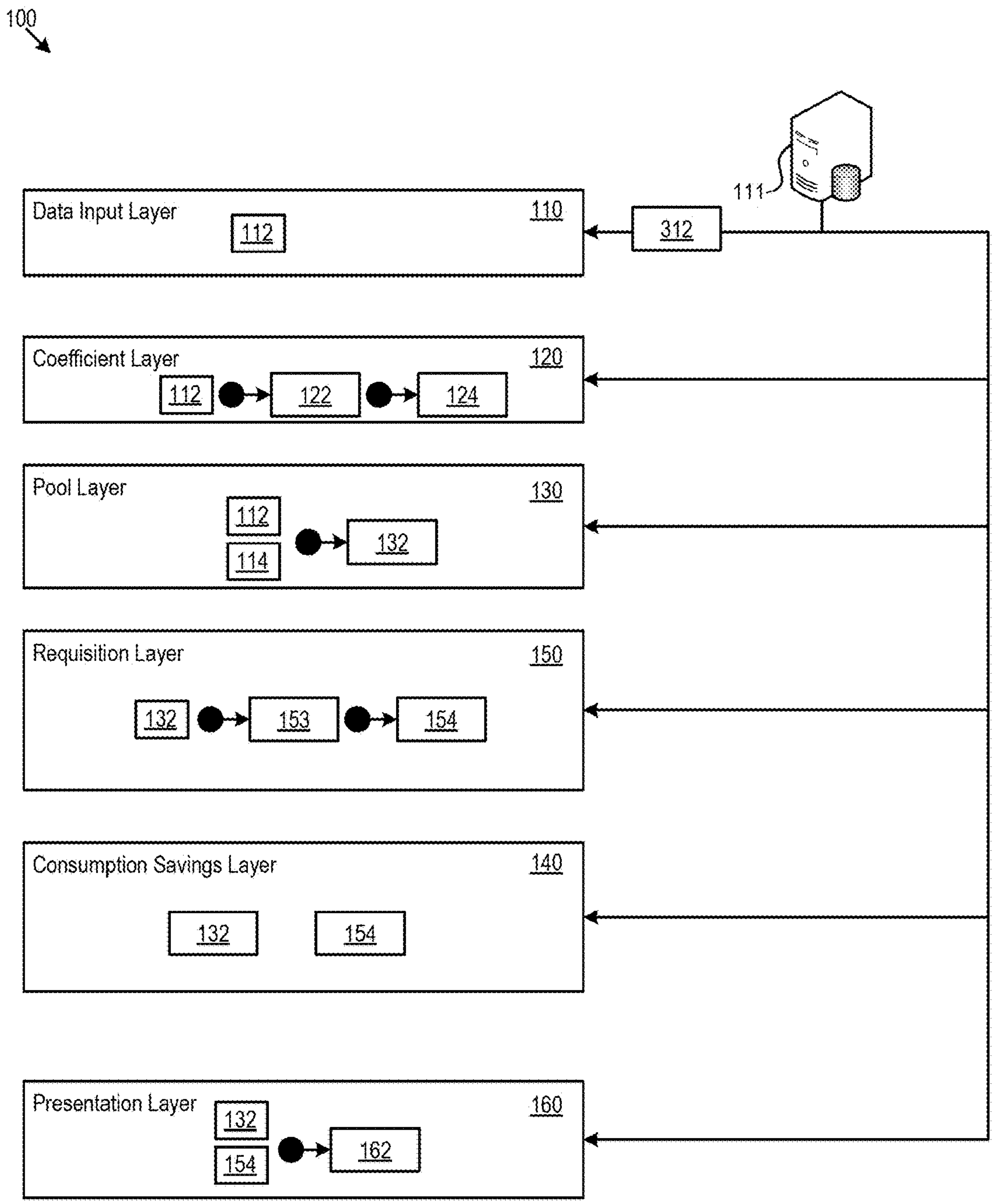

100
111
312
Data Input Layer
110
112
Coefficient Layer
120
112
122
124
Pool Layer
130
112
114
132
Requisition Layer
150
132
153
154
Consumption Savings Layer
140
132
154
Presentation Layer
160
132
154
162

Figure 1

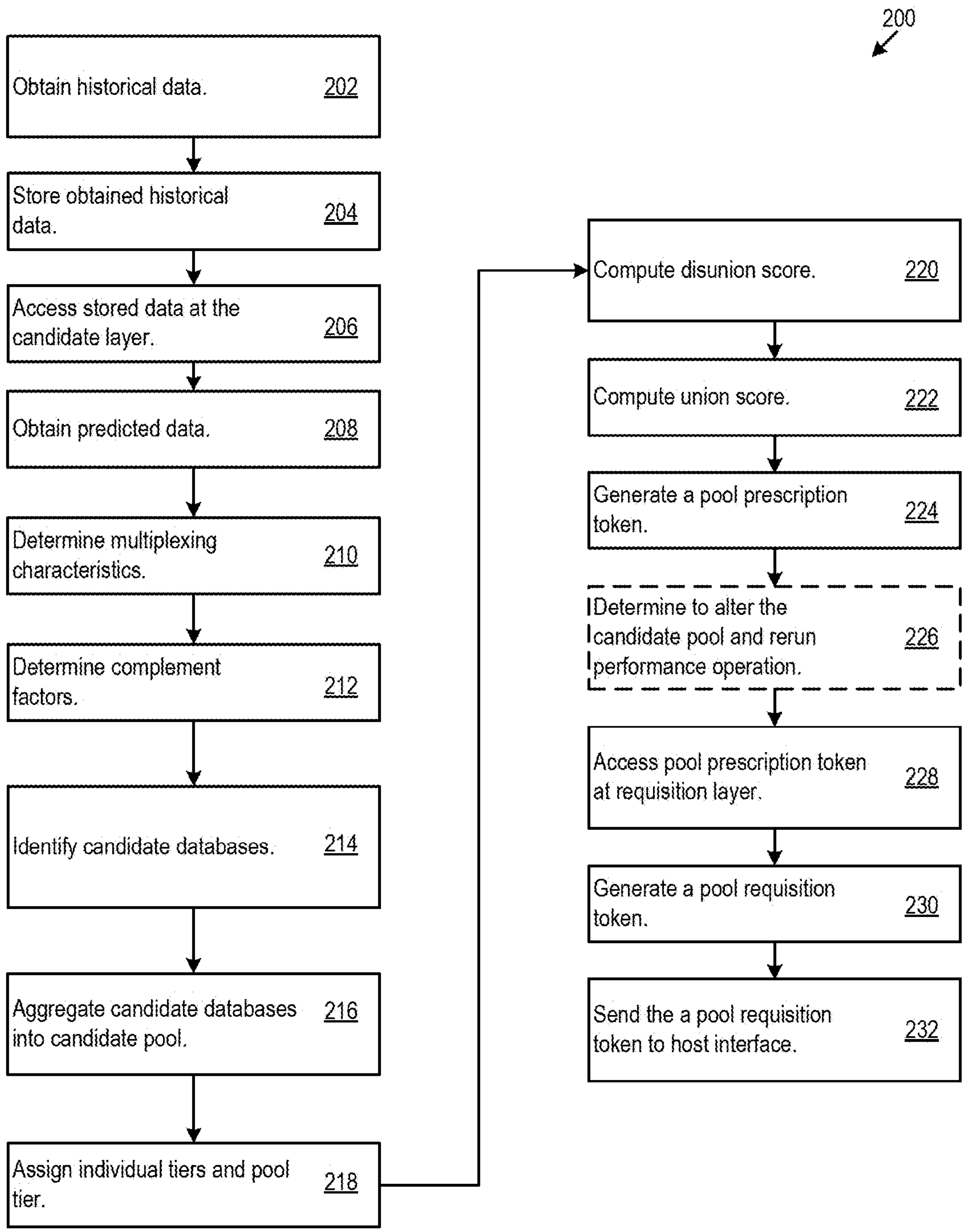

200
Obtain historical data. 202
Store obtained historical data. 204
Access stored data at the candidate layer. 206
Obtain predicted data. 208
Determine multiplexing characteristics. 210
Determine complement factors. 212
Identify candidate databases. 214
Aggregate candidate databases into candidate pool. 216
Assign individual tiers and pool tier. 218
Compute disunion score. 220
Compute union score. 222
Generate a pool prescription token. 224
Determine to alter the candidate pool and rerun performance operation. 226
Access pool prescription token at requisition layer. 228
Generate a pool requisition token. 230
Send the a pool requisition token to host interface. 232

Figure 2

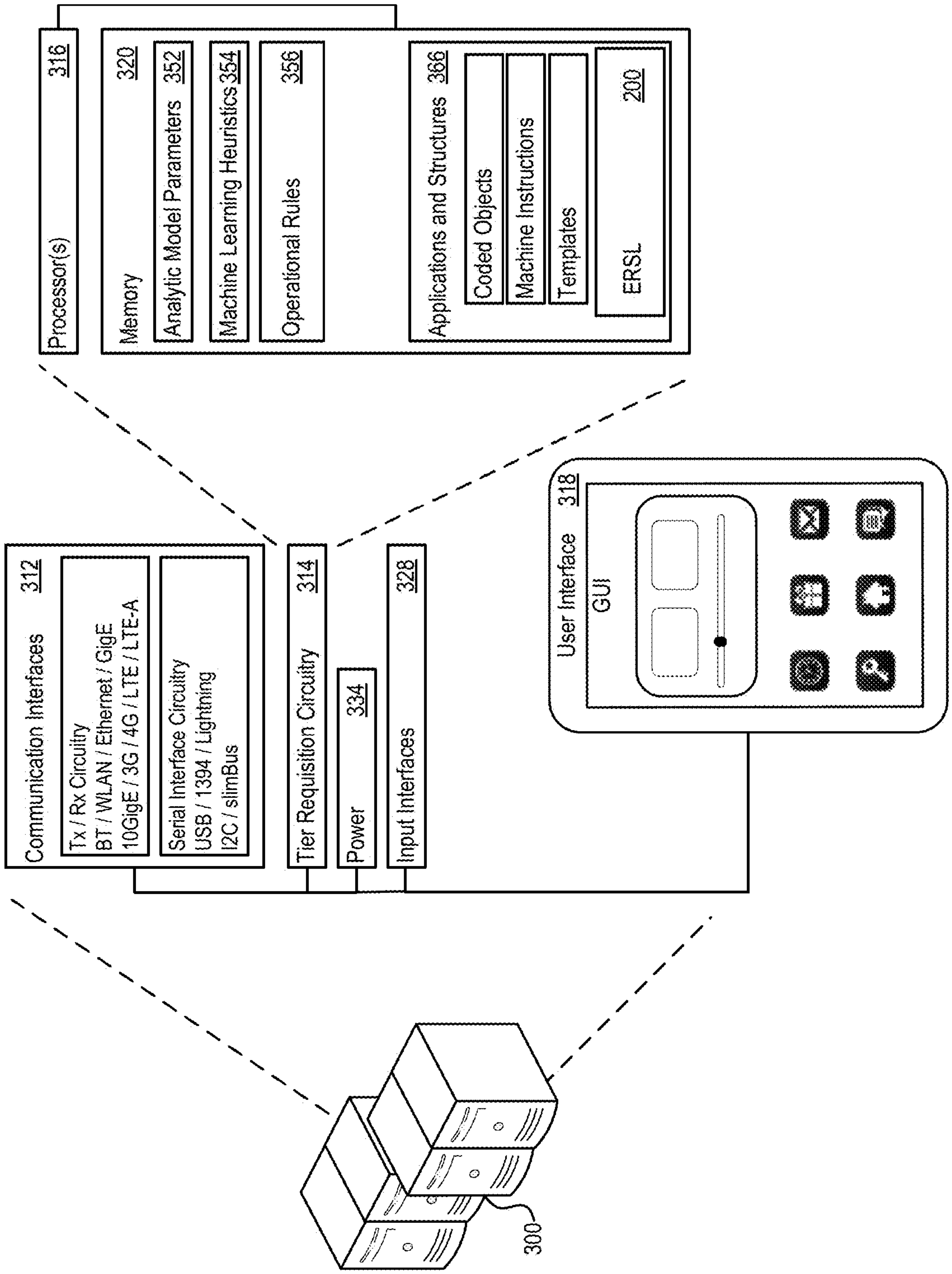

Processor(s) 316
Memory 320
Analytic Model Parameters 352
Machine Learning Heuristics 354
Operational Rules 356
Applications and Structures 366
Coded Objects
Machine Instructions
Templates
ERSL 200
Communication Interfaces 312
Tx / Rx Circuitry
BT / WLAN / Ethernet / GigE
10GigE / 3G / 4G / LTE / LTE-A
Serial Interface Circuitry
USB / 1394 / Lightning
I2C / slimBus
Tier Requisition Circuitry 314
Power 334
Input Interfaces 328
User Interface 318
GUI
300

Figure 3

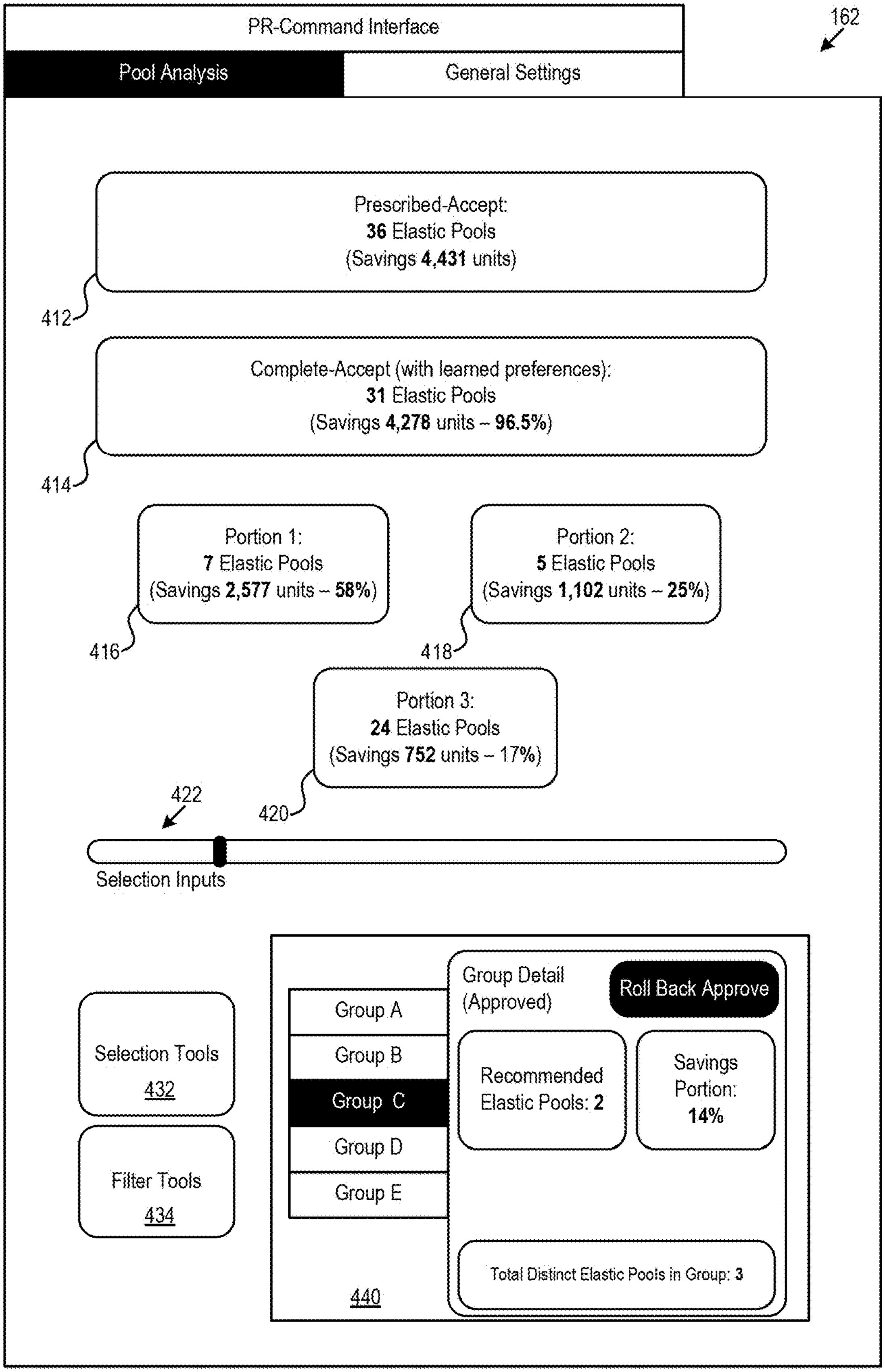

162
PR-Command Interface
Pool Analysis
General Settings
Prescribed-Accept:
36 Elastic Pools
(Savings 4,431 units)
412
Complete-Accept (with learned preferences):
31 Elastic Pools
(Savings 4,278 units – 96.5%)
414
Portion 1:
7 Elastic Pools
(Savings 2,577 units – 58%)
416
Portion 2:
5 Elastic Pools
(Savings 1,102 units – 25%)
418
Portion 3:
24 Elastic Pools
(Savings 752 units – 17%)
420
422
Selection Inputs
Selection Tools
432
Filter Tools
434
Group A
Group B
Group C
Group D
Group E
440
Group Detail
(Approved)
Roll Back Approve
Recommended
Elastic Pools: 2
Savings
Portion:
14%
Total Distinct Elastic Pools in Group: 3

Figure 4

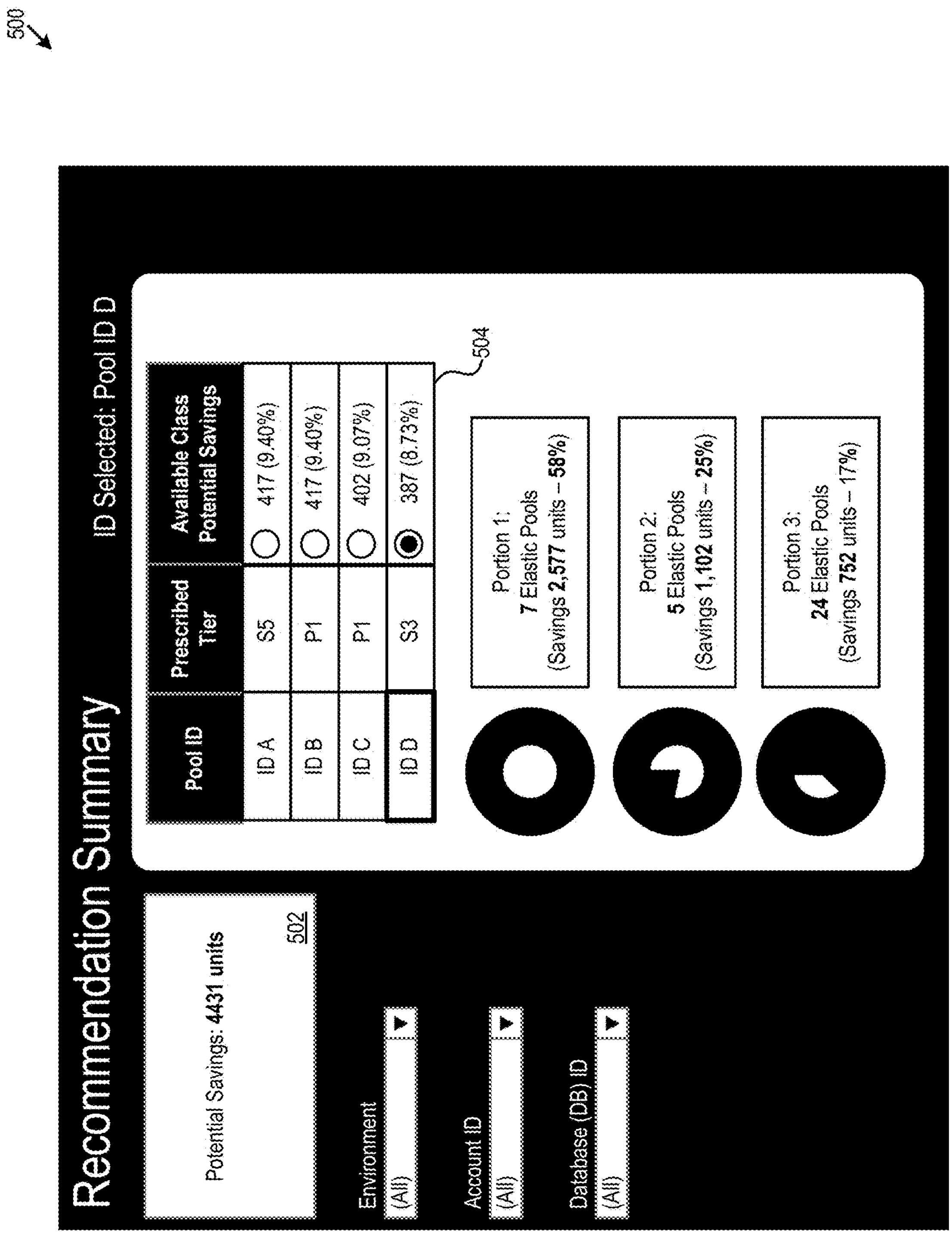

500
Recommendation Summary
ID Selected: Pool ID D
Potential Savings: 4431 units
502
Environment
(All)
Account ID
(All)
Database (DB) ID
(All)
Pool ID
Prescribed Tier
Available Class Potential Savings
ID A
S5
417 (9.40%)
ID B
P1
417 (9.40%)
ID C
P1
402 (9.07%)
ID D
S3
387 (8.73%)
504
Portion 1:
7 Elastic Pools
(Savings 2,577 units – 58%)
Portion 2:
5 Elastic Pools
(Savings 1,102 units – 25%)
Portion 3:
24 Elastic Pools
(Savings 752 units – 17%)

Figure 5

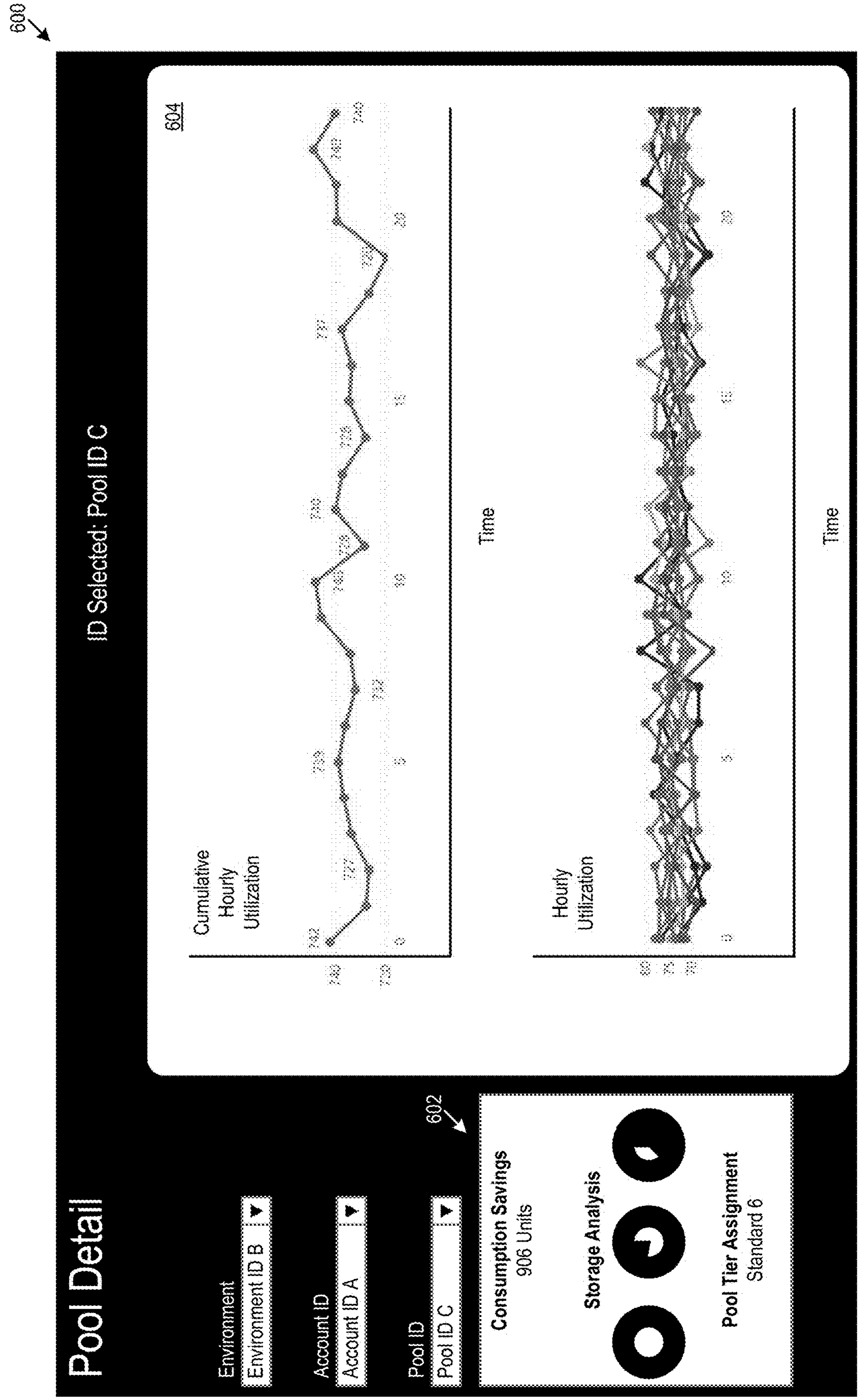

600
Pool Detail
Environment
Environment ID B
Account ID
Account ID A
Pool ID
Pool ID C
602
Consumption Savings
906 Units
Storage Analysis
Pool Tier Assignment
Standard 6
ID Selected: Pool ID C
604
Cumulative Hourly Utilization
Time
Hourly Utilization
Time

Figure 6

PRESCRIPTIVE ANALYTICS BASED MULTI-TIER ELASTIC-POOL DATABASE REQUISITION STACK FOR CLOUD COMPUTING

TECHNICAL FIELD

This disclosure relates to database-compute tier requisition via a prescriptive analytics based tier requisition stack.

BACKGROUND

Rapid advances in communications and storage technologies, driven by immense customer demand, have resulted in widespread adoption of cloud systems for managing large data payloads, distributed computing, and record systems. As one example, modern enterprise systems presently maintain data records many petabytes in size in the cloud. Improvements in tools for cloud resource allocation and consumption prediction will further enhance the capabilities of cloud computing systems.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** shows an example multiple-layer elastic requisition stack.

FIG. **2** shows example elastic requisition stack logic.

FIG. **3** shows an example specific execution environment for the elastic requisition stack.

FIG. **4** shows an example pool requisition-command interface.

FIG. **5** shows a second example pool requisition-command interface.

FIG. **6** shows a third example pool requisition-command interface.

DETAILED DESCRIPTION

In cloud computing systems, database-compute resources (e.g., database processor resources, data transaction resources, database connection resources, data transfer throughput resources, or other database-compute resources) may be requisitioned e.g., from database-compute providers such as Azure or other database systems. Various different implementations may provide tiered database-compute offerings where the various tiers provide database-compute resources covering various activity levels as indicated by activity factors. Activity factors may be determined using a combination (e.g., weighted sum, weighted average, sum average, or other weighted/non-weighted combination) of database-compute data type activity coefficients (e.g., indications of database-compute activity in various types, such as processor utilization data types, database-compute operation-rate data types, flush volume data types (e.g., log flush), and/or other database-compute activity data types).

In some cases, a requisition at a particular data tier may represent on underprovision or overprovision of an allowed activity for a particular database-compute system. Although, for example, a given tier may accommodate activity levels for one type of activity. For example, a requisitioned database-compute tier may appropriately support one or more activity level types for a given system. However, other activity types may not necessarily be adequately supported. For example, a given database-compute tier may offer activity levels that reflect processor utilization activity levels, but inadequately address activity levels as indicated by log flush data and/or operation-rate (e.g., database connection/session/transaction operate-rates). In another example, a flush data alone might indicate an activity level that is unduly high given comparatively low processor activity for the example system. Thus, consideration of multiple indications of activity level may reduce the risk of underprovision or overprovision. Further, resources dedicated to the overprovisioning of the requisitioned database-compute tier (that does not improve computing performance) could instead be applied to other computing resources that may improve computing performance of the system (as a whole) including, in some cases, non-database compute computing resources. Conversely, an underprovisioned database-compute tier may be operated continually at (or over) capacity and may be unable to fulfill database-compute operations without latency, connection/session backlog accumulation, or other degraded performance. Accordingly, an overprovisioned or underprovisioned database-compute tier may lead to performance degradation or inefficient deployment of hardware resources.

Accordingly, increased database-compute tier requisition accuracy provides a technical solution to the technical problem of system inefficiency by increasing the utilization and efficiency of cloud-based database-compute system.

In addition to tier provisioning, databases may share database-compute resources in elastic pools. Because simultaneous peak activity for different databases may be a rare coincidence in some database use contexts, multiple different databases with similar peak database-compute usage (e.g., maximum utilization, above threshold utilization, or other peak utilization) may be multiplexed on to the same pool of database-compute resources. Similar to the efficiencies gained through the statistical multiplexing of multiple television and/or data streams on to single communication channels, multiplexing databases on to a shared set of computing resources allows multiple databases to be serviced with peak database-compute resources that are less than the sum of all the peaks of the individual multiplexed databases. For example, if a first database has a short peak of 100% utilization and 0% utilization at all other times, it may be multiplexed with a second database that also has a short peak of 100% utilization and 0% at all other times. Rather, than using a database-compute capacity double that of the two databases, the multiplexed databases can operate with the same database-compute capacity as a single one of individual databases, assuming the two 100% peaks do not overlap in time.

Accordingly, the architectures and techniques discussed improve the efficiency of the underlying hardware of database-compute systems by prescriptively identifying candidate databases for multiplexing into elastic pools. Further the architectures and techniques discussed solve the technical problem of under-utilized provisioned database-compute resources through application of statistical multiplexing (e.g., selection and aggregation of candidate databases into elastic pools).

The tier requisition stack techniques and architectures described in U.S. patent application Ser. No. 16/897,906, filed Jun. 10, 2020, titled Prescriptive Analytics Based Multi-Parametric Database-Compute Tier Requisition Stack for Cloud Computing, and incorporated by reference in its entirety herein, may be used to prescribe database-compute tier requisitioning. The tier requisition stack described therein may provide prescriptive analytical database-compute tier correction taking into account allowed database-compute operation-rates, processor utilization patterns, flush data, concurrent session data, concurrent request data, online transaction processing (OLTP) storage requirements, and/or other data. Thus, the disclosed tier requisition stack techniques computing efficiency/accuracy and provide an improvement over existing solutions. Further, the tier requisition stack techniques and architectures provide a practical solution to the technical problem of efficient storage volume provision. Accordingly, activity factors, database-compute tolerances, and/or other factors used in database-compute tier selection may be determined by implementing the tier requisition stack described therein.

Additionally or alternatively to database-compute tier selection, databases may be aggregated into elastic pools that share database-compute resources. Elastic requisition stack architectures and techniques may use historical data which may include allowed database-compute operation-rates, processor utilization patterns, flush data, and/or other data; and tolerance data that may include concurrent session data, concurrent request data, online transaction processing (OLTP) storage requirements, and/or other data. In some implementations, the elastic requisition stack architectures and techniques may analyze expenditure report data (e.g., consumption metric data) for database-compute resource use: processor activity, memory usage history, storage volume input/output operation history. Furthermore, layers (such as predictive engine layers) may use computing cycles, data throughput, or other utilization metrics, seasonal usage cycles e.g., holiday schedules, daily usage cycles, weekly usage cycles, quarterly usage cycles or other data to forecast future usage. Additionally or alternatively, consumption metric data may include computing resource specific cost metrics such as expenditure-per-time or resource-per-time metrics.

FIG. **1** shows an example multiple-layer elastic requisition stack **100**, which may execute on elastic requisition circuitry making up the hardware underpinning of the elastic requisition stack **100**. In this example, the elastic requisition stack **100** includes, a data input layer **110**, a candidate layer **120**, a pool layer **130**, a requisition layer **150**, a consumption savings layer **140**, and a presentation layer **160**. The elastic requisition stack **100** may include a multiple-layer computing structure of hardware and/or software that may provide prescriptive analytical recommendations (e.g., prescriptive allowed operation-rates) through data analysis.

A stack may refer to a multi-layered computer architecture that defines the interaction of software and hardware resources at the multiple layers. The Open Systems Interconnection (OSI) model is an example of a stack-type architecture. The layers of a stack may pass data and hardware resources among themselves to facilitate data processing. As one example for the elastic requisition stack **100**, the data input layer **110** may provide the candidate layer **120** with data access resources to access historical data-types e.g., via storage and/or network hardware resources. Hence, the data input layer **110** may provide a hardware resource, e.g., memory/network access resources, to the candidate layer **120**. Accordingly, the multiple-layer stack architecture of the elastic requisition stack may improve the functioning of the underlying hardware.

In the following, reference is made to FIG. **1** and the corresponding example elastic requisition stack logic (ERSL) **200** in FIG. **2**. The logical features of ERSL **200** may be implemented in various orders and combinations. For example, in a first implementation, one or more features may be omitted or reordered with respect to a second implementation. At the input layer **110** of the elastic requisition stack **100**, the ERSL **200** may obtain historical data **112** (**202**) and then store the historical data **112** (**204**). In some cases, historical data **112** may be received via communication interfaces (e.g., communication interfaces **312**, discussed below). The historical data **112** may be accessed at least in part, e.g., via the communication interfaces **312**, from data sources **111**, which may include, database-compute utilization history databases, cloud expenditure databases, master virtual machine cost databases, use-history databases, storage access logs, virtual machine family/template description data, or other data sources. The historical data **112** may be provided by database-compute history databases, cloud expenditure databases, committed-use history databases, or other utilization data sources. The further data to support analysis may be provided by client preferences, service logs, description data, queries, or other database-compute data sources. Consumption metric data, as discussed below, may be obtained from cloud expenditure databases, master database-compute cost databases, expenditure histories, or other consumption metric data sources.

After the historical data, including various data types, such as processor utilization type data detailing processor usage over time, operation rate date detail rates and time-transaction-densities of database-compute operations/transactions, flush data detailing flushes of logs or other flushes, and/or other data, is obtained and stored the ERSL **200** at candidate layer of the elastic requisition stack may access the historical data (**206**).

The ERSL **200** may, at the candidate layer **120** of the elastic requisition stack, perform a deep-learning analysis of the historical data to obtain predicted utilization data **122** (**208**). For example, the candidate layer **120** may train a deep-learning (or other machine-learning algorithm) using the historical data. The trained algorithm may then be used to predict future utilization data for each of the data types. The predicted utilization data may be used to determine a predicted mapping for the data types. The predicted mapping may be used to determine a predicted activity factors and/or database-compute tiers. The predicted database-compute tier **164** may be used to determine a future tier recommendation for selection of similarly-tiered candidates for elastic pools and/or comparison of individual compute performance against pooled performance.

In some cases, the forecasted utilization data accuracy may fall below a desired level. After training a model (such as a deep learning model or machine learning model), the ERSL **200** may determine accuracy be generating predicted utilization data for a past period for which historical utilization data is available or later comparing predicted future values to eventual measured values. In some cases, recent historical data may be compared to upcoming predicted data (such as in the pseudocode below). The ERSL **200** may compare the predicted data to the measured/historical data and determine the accuracy of the model. Other measure of accuracy may be used, for example model confidence measures or other accuracy measures. When the accuracy of the model falls below a desire level (for example, an accuracy threshold) the ERSL **200** may forgo reliance on predicted utilization data from the candidate layer. The ERSL may also determine a historical mapping based on historical data.

In some implementations, the ERSL **200** may perform a context-based machine learning model selection. For example, a deep learning model may be selected when a single utilization metric (or number below a defined threshold) is being predicted. For example, a tree-based algorithm may be selected when multiple utilization metrics (or number above a defined threshold) are being predicted. In some cases, other combinations of models and conditions may be defined for the context-based model selection. For example, for upper and/or quantiles this context-based selection may rely on selection of the model with the lowest quantile loss function.

The ERSL **200** may, based on the historical data and the predicted (e.g., forecasted) data, determine historical and predicted multiplexing characteristics for databases that may potentially be pooled (**210**). In some cases, multiplexing characteristics may include ratios of peak database-compute utilization to average (e.g., mean, median, inner quartile, or other average metric) database-compute utilization. Databases for which provisioned database-compute resources go used for a majority of the evaluation period may have potential for efficiency increase through multiplexing with other such databases. In some cases, databases with sparse (e.g., from a mathematical standpoint) peaks may have potential for efficiency increase because the chance of peak utilization coincidence for mathematically sparse systems is low.

After determining historical and predicted multiplexing characteristics for the databases that may be potentially pooled, the ERSL **200** may determine complement factors **124** among the databases (**212**). Complement factors may include features of the activity mappings and/or multiplexing characteristics that may cause two or more databases to be well-suited complements for multiplexing for one another. For example, a complement factor may include a determination that two or more databases have similar peak-to-average utilization ratios. For example, a complement factor may include a determination that two or more databases a level of mathematical sparseness that would facilitate multiplexing the two or more databases while keeping the probability of peak coincidence below a threshold level. For example, a complement factor may include the determination that two databases exhibit time-based orthogonality in usage. For example, a first database may have peaks only at night (or other identifiable period) while a second database (with usage orthogonal to the first) only has peaks during the day (or outside of the identifiable period). A complement factor may include features between two or more databases that are consistent with efficiency gain through statistical multiplexing of the databases on to shared database-compute resources.

Based on the multiplexing characteristics (e.g., predicted and/or historical) and complement factors, the ERSL **200** may identify multiple candidate databases for inclusion into a candidate pool (**214**). The ERSL **200** may aggregate the multiple candidate databases to the candidate pool (**216**) for pooled analysis.

Table 1 shows example pseudocode for selection of candidate databases based on historical data.

TABLE 1

Selection of Candidate Databases based on Historical Data
Historical Selection Criteria (ϕ) = IF (((π >= Ω) & (δ >= Ω)) & ((μ >= χ) & (ρ >= χ)) THEN "Candidate Selected" ELSE "Not Selected") - EQUATION 1A
Where,
π = Max database-compute/Average database-compute utilization ratio (90-day window)
Ω = Tunable Parameter. Recommended Value = 1.5
δ = Max Concurrency/Average Concurrency utilization ratio (90-day window)
μ = Max database-compute/90^{th} Percentile database-compute utilization ratio (90-day window)
χ = Tunable Parameter. Recommended Value = 1.4
ρ = Max Concurrency/90^{th} Percentile Concurrency utilization ratio (90-day window)

Table 2 shows example pseudocode for selection of candidate databases based on predicted data.

TABLE 2

Selection of Candidate Databases based on Predicted Data
Predicted Selection Criteria (ϕPred) = IF (((πPred >= Ω) & (δPred >= Ω)) & ((μPred >= χ) & (ρPred >= χ)) THEN "Candidate Selected" ELSE "Not Selected")
[Such that the Quantile loss is <= ξQuantile Loss] - EQUATION 1B
Where,
πPred = Max database-compute/50th percentile predicted database-compute utilization ratio (90-day window)
Ω = Tunable Parameter. Recommended Value = 1.5
δPred = Max Concurrency/50th percentile predicted Concurrency utilization ratio (90-day window)
μPred = Max database-compute/90th Percentile Predicted database-compute utilization ratio (90-day window)
χ = Tunable Parameter. Recommended Value = 1.4
ρPred = Max Concurrency/90th Percentile Predicted Concurrency utilization ratio (90-day window)
ξQuantile Loss = Threshold for Quantile Loss

Table 3 shows example pseudocode for selection of candidate databases based on a combined data.

TABLE 3

Selection of Candidate Databases based on Combined Data
Final Selection Condition = If ((ϕ_{Pred} = "Candidate Selected" & ϕ = "Candidate Selected") THEN "Candidate Selected" ELSE "Not Selected") - EQUATION 1C

For each of multiple candidate databases, ERSL **200** may determine a database-compute tier based on the corresponding activity factors of the individual databases (**218**). Then, the ERSL **200** may assign a database compute pool tier consistent with the individual tiers (**218**). For example, in various cloud systems, the candidate pool tier may be equal to or greater than the tier of the highest tier individual candidate database in the pool. For example, setting the candidate pool tier equal to or greater than the tier of the highest tier individual candidate database in the pool may allow for sufficient database-compute resources to meet the demand created by highest tier individual candidate database. In some cases, the candidate pool tier may be set greater than the tier of the highest tier individual candidate database to account for a probability of peak utilization coincidence among the pooled databases.

Table 4 shows example pseudocode for tier selection.

TABLE 4

Tier Selection
i = Class (n)
Σ (Max database-compute) = ξPool(i) - EQUATION 2A (Max cumulative database-compute for 90 day window for the pool)
i = Class1
i = Class (n)
Σ (Max Concurrency) = τPool(i) - EQUATION 2B (Max cumulative Concurrency for 90 day window for the pool)
i = Class1
i = Class (n)
Σ (Storage) = ΨPool(i) - EQUATION 2C (Cumulative Storage for the pool)
i = Class1
Pool Tier Recommendation (σedatabase-compute_TierIndex(i)) = If (κLow_TierIndex(i) <= ξPool(i) <= κHigh_TierIndex(i) THEN "TIER_INDEX(i)" ELSE "NOT APPLICABLE" - EQUATION 2D
Pool Tier Recommendation (σeConcurrency_TierIndex(i)) = If (λLow_TierIndex(i) <= τPool(i) <= λHigh_TierIndex(i) THEN "TIER_INDEX(i)" ELSE "NOT APPLICABLE" - EQUATION 2E

TABLE 4-continued

Tier Selection
Where,
κLow_TierIndex(i) = Lower database-compute limit for the identified database-compute Tier
κHigh_TierIndex(i) = Upper database-compute limit for the identified database-compute Tier
λLow_TierIndex(i) = Lower Concurrency limit for the identified database-compute Tier
λHigh_TierIndex(i) = Upper Concurrency limit for the identified database-compute Tier

At the pool layer **130**, the ERSL **200** may compare the database-compute performance of the candidate pool versus the individual candidate databases. To perform the comparison, the ERSL **200** may perform a performance score operation by computing a disunion score (**220**) and a union performance score (**222**). A performance score may be based on the amount of database-compute resources allocated to service an individual database or pool of databases. In some cases, an allocation of more computing resources may make a performance score worse. As discussed herein, a first performance score that 'exceeds' a second performance score is better than the second, regardless of the way a particular scoring system attaches raw numbers to performance. The calculation of the performance score may be based on the determined database-compute tiers of the individual databases. In some cases, the performance score may take into account consumption metric data.

In some cases, because pooling may allow shared database-compute resources, resources that experience dynamic usage (e.g., processing, random access memory (RAM), concurrent connections, or other dynamic use resources may have more efficiency gains relative to shared static resources, such as storage. In an illustrative example scenario, five databases may readily share the peak processing capacity of a single database because the five databases may not necessarily utilize processor activity at some time (e.g., the databases may have dormant periods). The storage used by the databases may increase with their number, because (in the example scenario) the databases use storage at all times (regardless of whether the databases are active). In some cases, a pool may include additional storage (and/or other static resources) provisioning to account for this difference between static and dynamic use resources.

Table 5 shows example psedocode for determining storage demand.

TABLE 5

Storage Demand Determination
i = Class (n)
Σ (Max database-compute) = ξPool(i) - EQUATION 2A (Max cumulative database-compute for 90 day window for the pool)
i = Class1
Extra Storage (νExtraStorage) = IF(ΨPool(i) <= Ø THEN 0 ELSEIF ((ΨPool(i) > Ø) OR (ΨPool(i) <= ØMax) THEN (ΨPool(i) − Ø) ELSE (ΨPool(i) − ØMax))) - EQUATION 3A
Storage Tier (νTier) = IF((νFamily = "Basic", νExtraStorage > 0) THEN "Next Basic Tier" ELSEIF ((νFamily <> "Basic" AND (νExtraStorage + Ø) <= ØMax) THEN σeDTU_TierIndex(i) ELSE "Next Tier")) - EQUATION 3B
Extra Storage Cost (νExtraStorageCost) = IF((νExtraStorage > 0 & νFamily = "Basic") then 0 ELSEIF ((νExtraStorage > 0 & νFAMILY = "Standard") THEN (0.221 * νExtraStorage) ELSEIF ((νExtraStorage > 0 & νFamily = "Premium") THEN (0.441 * νExtraStorage) ELSE 0))) - EQUATION 3C
Where, Ø = Included Storage for the Tier, ØMax = Max Storage for the Tier

For the performance score operation, the ERSL **200** may compute a union performance score (**222**) that is based on the performance of the candidate databases while pooled. The calculation of the performance score may be based on the assigned database-compute tier of the candidate pool. In some cases, the performance score may take into account consumption metric data which may be separately defined for pooled operation.

When the union performance score exceeds the disunion score, the ERSL **200** may generate a pool prescription token **132** (**224**). A token may include a set requests or commands for a host interface for cloud computing requisition system. Thus, a token may include code, scripts, or other commands that requisition database-compute resources when sent to the host interface. The pool prescription token, may include a set of commands that requisitions the candidate pool in the form in which its performance score exceeded the disunion score for unpooled operation.

Table 6 shows example psedocode for determining database-compute performance for pooled operation and validation for database-compute tolerances.

TABLE 6

Pooled Performance Determination and Validation
Validation Check (VC1) = If ((ξPool(i) <= ØRecommended_DTU_Max) & (τPool(i) <= ØRecommended_CONCURRENT_Max) & (ØNo_DB <= ØMax_No_DB_Pool) & (ΨPool(i) <= ØMax) THEN "Proceed for further analysis" ELSE "Reject Candidate") - EQUATION 4A
Where,
ØRecommended_DTU_Max = Maximum DTU limit for the recommended pool
ØRecommended_CONCURRENT_Max = Maximum Concurrency limit for the recommended pool
ØNo_DB = No of DB's in the pool
ØMax_No_DB_Pool = Maximum DB's allowed for the recommended pool
eDTU Validator (ß) = IF(VC1 = "Proceed for further analysis" THEN (ELSEIF ((ξPool(i) * ξBUFFER <= ØRecommended_DTU_Max) THEN "Accept" ELSE "Reject") ELSE "Reject")) - EQUATION 4B
eDTU Frequency Validator (θ) = IF(VC1 = "Proceed for further analysis" THEN (ELSEIF ((ξHigh_Utilization_Frequency/ξCount_DTU_Array) <= ØBuffer) THEN "Accept" ELSE "Reject") ELSE "Reject")) - EQUATION 4C
Where,
ξBUFFER and ØBuffer can be tuned. Recommended value is 10%
ξHigh_Utilization_Frequency = Number of DTU Utilization readings above 80% of ØRecommended_DTU_Max
ξCount_DTU_Array = No of DTU utilization readings
Final Decision = IF(Sum of Individual DB Rate > eDTU Pool Rate THEN "AcceptPool" ELSE "RejectPool")

When the disunion performance score exceeds the union performance score, the ERSL **200** may determine to alter the candidate pool and rerun the performance score operation (**226**). For example, for each iteration, the ERSL **200** may iteratively eliminate one or more of the candidate databases from the candidate pool and rerun the performance score operation (e.g., calculate new disunion and union performance scores each iteration) until a candidate pool for which the union performance score exceeds the corresponding disunion performance score.

Table 7 shows example pseudocode determining a candidate database for elimination from candidate pool.

TABLE 7

Candidate Database Backward Elimination
Weighted Utilization Score (ω) = (($\xi_{Pool(i)}$ * 0.15) + (0.15 * ξ_{P95}) + (0.4 * ξ_{Mean}) + (0.3 * (1 + % of $\xi_{High\_Utilization\_Frequency}$) * $\xi_{Pool(i)}$)) - EQUATION 5A
The DB with the highest ω is eliminated from the pool till we reach ACCEPT code in 4A and 4B

In some cases, the individual candidate databases may be assigned an inclusion rank (e.g., a rank based on the multiplexing characteristics of the candidate database and/or the complement factors to which the candidate database contributes). The ERSL **200** may, in some cases, eliminate candidate databases with lower inclusion ranks may be eliminated before those with higher inclusion ranks.

If no subset of the original candidate database can form a pool with a union score that exceeds the corresponding disunion score, the ERSL **200** may generate a prescriptive token that requisitions unpooled operation for the candidate databases.

At the requisition layer **150**, ERSL **200** may access the pool prescription token (**228**). In some cases, as discussed below, the requisition layer **150** may pass the token to the presentation layer for generation of command interfaces to facilitate operator review of the elastic pool requisitions.

Table 8 shows an illustrative example implementation pseudocode for execution of an example system to determine elastic database computer tiers and pools in an example Microsoft Azure computing environment. However, other environments may be used.

TABLE 8

Illustrative Example Implementation Pseudocode
Input: Utilization Db, Billing Db, Cost Db, Features DB
Output: Pooling Recommendations for each DTU DB class
Step0: Load Azure Master Cost File
Step0a: Azure Intelligent Cost File Generation
Step1: Load the input files
Step2: Cleanse the data
Step2a: Select the required variables for analysis
Step2b: Rename the variables
Step2c: Format the variables (date, numeric and string)
Step3: Computing the maximum utilization
Step3a: for each resource id (1, n) sort utilization value by date and value
Step3b: for each resource id (1, n) select maximum value for each hour
Step4: Filtering billing data for relevant DTU db tiers
Step5: Merge Utilization, Billing, Cost Files and Feature File
Step5a: Merge Utilization and Billing files by resource id
Step5b: Merge the output of Step5a with the Cost file (to get the cost info for DTU at specific region)
Step6: Calculating the nth percentile utilization value
Step6a: Calculate the nth percentile (typically 90th and 95th) values for DTU and Concurrent Requests for each resource id (1, n)
Step6b: Calculate the mean values for DTU and Concurrent Requests for each resource id (1, n)
Step7: Candidate Selection based on Historical data - Equation 1A
Step7a: Using the Maximum, 90th percentile and Average utilization analysis for each resource id (1, n), select the databases that have sporadic high utilization
Step8: Candidate Selection based on ML Predictions - Equation 1B
Step8a: Select the right algorithm from and ensemble of algorithms depending on the "percentile" to be predicted and the number of variables in the prediction equation
Step8b: Compute the 50th, 90th and the 100th percentile values on a moving window basis for the next 15 days
Step8c: Select the candidates bases on the utilization pattern within an accept "quantile loss"
Step9: Final selection criteria based on Historical and Predicted data - Equation 1C

TABLE 8-continued

Illustrative Example Implementation Pseudocode
Step10: Pooling Selection: Computing the Pools within Class - Equation 2
Step10a: Compute the Maximum "overlapping/concurrent" DTU and Concurrent Requests for the eDTU class/pool Equation 2A and 2B
Step10b: Compute the Consumed Storage for every identified eDTU pool Equation 2C
Step11: Pool Tier Identification: - Equation 2D/2E
Step11a: Based on the Computed values in equation 2A and 2B, identify the precise Index for the DTU and Concurrent Requests at pool level
Step12: Extra Storage Provisioning, Tier and Cost Computations: - Equation 3
Step12a: Compute the extra storage (if required) for the proposed pool tier over and above the included/default storage - Equation 3A
Step12b: Depending on the identified Pool Tier and the used storage, identify the Storage Tier - Equation 3B
Step12c: Compute the extra storage cost as computed by equation 3A and 3B - Equation 3C
Step13: Utilization Matrix Analysis (UMA) - Equation 4
Step13a: Initial Candidate selection based on Utilization and Pool constraint analysis - Equation 4A
Step13b: Level 1 validator based on maximum observed cumulative eDTU for the pool (inclusive of buffer) - Equation 4B
Step13c: Level 2 validator based on frequency of high concurrent eDTU values for the pool (inclusive of buffer) - Equation 4C
Step14: Backward Utilization Elimination (BAE) - Equation 5
Step14a: The DB with the highest ω is eliminated from the pool till we reach ACCEPT code in 4A and 4B - Equation 5A
Step15: Final Pool Tier Selection - Equation 6

In various implementations, responsive to the pool prescription token, the ERSL **200** may receive one or more finalization directives. The finalization directive **153** may, for example, include commands received from an operator via a pool requisition (PR)—command interface **162** generated at the presentation layer **160**. The commands may change and/or confirm the selection of the candidate pool. The finalization directive may, for example, include feedback-based machine-learning-trained (e.g., using various machine-learning schemes, deep-learning, neural networks, and/or other machine-learning schemes) adjustments to the candidate pool. The feedback (on which to base the machine-learning training) may include operator commands, for example, those received at the PR-command interface **162**.

Based on the finalization directive **153**, ERSL **200** may generate a pool requisition token **154** (**230**). The pool requisition token **154** may, in some cases, designate a request for a pool identical to that in the pool prescriptive token. In some cases where the finalization directive indicates a change relative to the pool prescriptive token, the pool requisition token **154** may designate a request for a pool that differs from that in the pool prescriptive token.

After generating the pool prescriptive token **154**, the ERSL **200** may send the pool requisition token **154** (**232**) to a host interface that controls reservation and/or requisition of data-compute resources to execute the request for the pooled databases.

In some implementations, ERSL **200**, at the consumption savings layer **140**, may obtain consumption metric data to determine a consumption rate/level for unpooled and/or pooled operation for a given set of candidate databases in a candidate pool. The ERSL **200** may compare consumption for pooled and unpooled operation to determine a pool consumption savings for transitioning to pooled operation.

FIG. **3** shows an example specific execution environment **300** for the tier requisition stack **100** described above. The execution environment **300** may include tier requisition circuitry **314** to support execution of the multiple layers of elastic requisition stack **100** described above. The tier requisition circuitry **314** may include processors **316**, memory **320**, and/or other circuitry.

The memory **320** may include analytic model parameters **352**, machine learning heuristics **354**, and operational rules **356**. The memory **320** may further include applications and structures **366**, for example, coded objects, machine instructions, templates, or other structures to support historical data analysis, pool candidate selection/evaluation or other tasks described above. The applications and structures may implement the ERSL **200**.

The execution environment **300** may also include communication interfaces **312**, which may support wireless, e.g. Bluetooth, Wi-Fi, WLAN, cellular (4G, LTE/A), and/or wired, Ethernet, Gigabit Ethernet, optical networking protocols. The communication interfaces **312** may also include serial interfaces, such as universal serial bus (USB), serial ATA, IEEE 1394, lighting port, I^2C, slimBus, or other serial interfaces. The communication interfaces **312** may be used to support and/or implement remote operation of the PR-command interface **162**. The execution environment **300** may include power functions **334** and various input interfaces **328**. The execution environment may also include a user interface **318** that may include human-to-machine interface devices and/or graphical user interfaces (GUI). The user interface **318** may be used to support and/or implement local operation of the PR-command interface **172**. In various implementations, the elastic requisition circuitry **314** may be distributed over one or more physical servers, be implemented as one or more virtual machines, be implemented in container environments such as Cloud Foundry or Docker, and/or be implemented in Serverless (functions as-a-Service) environments.

In some cases, the execution environment **300** may be a specially-defined computational system deployed in a cloud platform. In some cases, the parameters defining the execution environment may be specified in a manifest for cloud deployment. The manifest may be used by an operator to requisition cloud based hardware resources, and then deploy the software components, for example, the elastic requisition stack **100**, of the execution environment onto the hardware resources. In some cases, a manifest may be stored as a preference file such as a YAML (yet another mark-up language), JSON, or other preference file type.

Referring now to FIG. **4**, an example PR-command interface **162** is shown. The PR-command interface **162** may include multiple selectable options **412**, **414**, **416**, **418**, **420**, **422** and data regarding the pool candidate selection/evaluation before and after alteration to accommodate the learned preferences of the operator. In this example scenario, the selectable options may include a prescribed-accept option **412** to implement some or all of the prescribed pool candidates (e.g., for multiple parallel analyses) as a group without alteration based on learned preferences, a complete-accept option **414** to implement the pool candidate selections (finalization directives) based on learned preferences, options **416**, **418**, **420** to implement augments to selected subsets of the pool candidates, option **422** to adjust preferences (e.g., selection inputs, threshold ratios, or other elastic requisition analysis inputs) and re-run the routine at the candidate and pool layers, or other selectable options to control finalized pool requisition token output.

Additionally or alternatively, the PR-command interface **162** may include selection and filter tools **432**, **434** to support granular manipulation of the prescribed pool candidates, e.g., by resource region, by pool size; or other granular manipulation.

In some implementations, the PR-command interface **162** may include a group detail panel **440** for management of group-level selectable options such as group level approvals of prescribed pool candidates. Additionally or alternatively, the group detail panel **440** may display group-level information regarding prescribed pool candidates. The group detail panel **440** may also provide an option to roll back previously approved pools.

In the example, shown in FIG. **4**, the options **416**, **418**, **420** allow for manipulation of selected subsets of the pools. For example, as shown the example routine in table two, the prescribed pool candidates may be "binned" into consumption savings classes. For example, "high", "medium", and "low" consumption savings bins may allow the operator to select specific groups prescribed pool candidates (e.g., as determined at the consumption savings layer **150**). The options **416**, **418**, **420** show the respective portions of the total consumption savings that may be achieved by adjusting each specific subset of the prescribed pool candidates. In the example, the first subset option **416** provides the greatest marginal consumption savings, while the options **418**, **420** provide successively smaller marginal consumption savings.

FIG. **5** shows a second example PR-command interface **500**. The second example PR-command interface **500** provides summary information panels **502** for overall efficiency achievements including consumption savings. The second example PR-command interface **500** may further provide detail information panels **504** with pool-identifier-specific details.

FIG. **6** shows a third example PR-command interface **600**. The third example PR-command interface **600** is pool identifier (e.g., a specific and/or unique designation for a given pooled resource) specific. The example PR-command interface may show a summary panel **602** that may include consumption savings or other details for the pool. The example PR-command interface may show a plot **604** of pooled database compute resources over time period that may include both historical and forecasted periods.

The methods, devices, processing, circuitry, and logic described above may be implemented in many different ways and in many different combinations of hardware and software. For example, all or parts of the implementations may be circuitry that includes an instruction processor, such as a Central Processing Unit (CPU), microcontroller, or a microprocessor; or as an Application Specific Integrated Circuit (ASIC), Programmable Logic Device (PLD), or Field Programmable Gate Array (FPGA); or as circuitry that includes discrete logic or other circuit components, including analog circuit components, digital circuit components or both; or any combination thereof. The circuitry may include discrete interconnected hardware components or may be combined on a single integrated circuit die, distributed among multiple integrated circuit dies, or implemented in a Multiple Chip Module (MCM) of multiple integrated circuit dies in a common package, as examples.

Accordingly, the circuitry may store or access instructions for execution, or may implement its functionality in hardware alone. The instructions may be stored in a tangible storage medium that is other than a transitory signal, such as a flash memory, a Random Access Memory (RAM), a Read Only Memory (ROM), an Erasable Programmable Read Only Memory (EPROM); or on a magnetic or optical disc, such as a Compact Disc Read Only Memory (CDROM), Hard Disk Drive (HDD), or other magnetic or optical disk; or in or on another machine-readable medium. A product, such as a computer program product, may include a storage medium and instructions stored in or on the medium, and the instructions when executed by the circuitry in a device may cause the device to implement any of the processing described above or illustrated in the drawings.

The implementations may be distributed. For instance, the circuitry may include multiple distinct system components, such as multiple processors and memories, and may span multiple distributed processing systems. Parameters, databases, and other data structures may be separately stored and managed, may be incorporated into a single memory or database, may be logically and physically organized in many different ways, and may be implemented in many different ways. Example implementations include linked lists, program variables, hash tables, arrays, records (e.g., database records), objects, and implicit storage mechanisms. Instructions may form parts (e.g., subroutines or other code sections) of a single program, may form multiple separate programs, may be distributed across multiple memories and processors, and may be implemented in many different ways. Example implementations include stand-alone programs, and as part of a library, such as a shared library like a Dynamic Link Library (DLL). The library, for example, may contain shared data and one or more shared programs that include instructions that perform any of the processing described above or illustrated in the drawings, when executed by the circuitry.

Various implementations may use the techniques and architectures described above. Table 9 includes various examples.

TABLE 9

Examples
E1. A system including: elastic requisition circuitry configured to execute an elastic requisition stack, the elastic requisition circuitry configured to: at a data input layer of the elastic requisition stack, obtain historical data including data types, the data types including processor utilization type data, operation rate type data, flush volume type data, or any grouping thereof; at a candidate layer of the elastic requisition stack: identify multiple candidate databases by: obtaining a historical multiplexing characteristic for each of the multiple candidate databases via a map of the historical data; via a deep-learning analysis of the historical data, obtaining a predicted multiplexing characteristic for each of the multiple candidate databases via a map of predicted activity; identifying a complement factor from among the historical multiplexing characteristics; predicted multiplexing characteristics; or both for the multiple candidate databases, the complement factor consistent with a least one statistical multiplexing efficiency among the multiple candidate databases; and aggregating the multiple candidate databases into a candidate pool based on the complement factor; for each of multiple candidate databases, determine a database-compute tier based on a corresponding activity factor, the corresponding activity factor based on the historical data for the individual one of the multiple candidate databases; and assign a candidate pool tier consistent with the database-compute tiers of the multiple candidate databases; at a pool layer of the elastic requisition stack: perform a performance score operation on the candidate pool by: computing a disunion performance score for unpooled operation of the individual ones of the multiple candidate databases; computing a union performance score for pooled operation of the multiple candidate databases; and at a time that the union performance score exceeds the disunion performance score, generating a pool prescription token for requisition of the candidate pool including the multiple candidate databases; at a requisition layer of the elastic requisition stack: responsive to the pool prescription token, receive a finalization directive; and based on the finalization directive, generate a pool requisition token; and

TABLE 9-continued

Examples
network interface circuitry configured to send the pool requisition token to a host interface for control of database-compute resources.
E2. The system of example E1 or any other example in this table, where the elastic requisition circuitry is further configured to, at the pool layer: at a time that the union performance score fails to exceed the disunion performance score: perform a pool revision operation on the candidate pool by: determining a revised candidate pool by removing a first candidate database of the multiple candidate databases from the candidate pool; perform the performance score operation on the revised candidate pool.
E3. The system of example E2 or any other example in this table, where the elastic requisition circuitry is further configured to, at the pool layer: iteratively perform performance score operations and pool revision operations until: union performance score exceeds the disunion performance score; or a current candidate pool includes a single candidate database.
E4. The system of example E2 or any other example in this table, where the elastic requisition circuitry is further configured to, at the pool layer: determine the first candidate database by identifying a lowest inclusion rank database of the multiple candidate databases.
E5. The system of example E4 or any other example in this table, where the elastic requisition circuitry is further configured to, at the candidate layer: determine an inclusion rank for each of the multiple candidate databases based on: the historical multiplexing characteristic for the candidate database; the predicted multiplexing characteristic for the candidate database; a complement factor relevant to the candidate database; or any grouping thereof.
E6. The system of example E1 or any other example in this table, where the elastic requisition circuitry is configured to, at a predictive engine layer of the elastic requisition stack: perform the deep-learning analysis of the historical data to obtain predicted utilization data including the data types; and determine the map of predicted activity based on the predicted utilization data.
E7. The system of example E6 or any other example in this table, where the elastic requisition circuitry is configured to, at the predictive engine layer, perform the deep-learning analysis of the historical data by training a deep learning algorithm using the historical data to obtain predicted utilization data.
E8. The system of example E1 or any other example in this table, where the elastic requisition circuitry is configured to, at a consumption savings layer of the elastic requisition stack: determine a pool consumption savings based on an amount by which the union performance score exceeds the disunion performance score.
E9. The system of example E8 or any other example in this table, where the elastic requisition circuitry is configured to, at a presentation layer of the elastic requisition stack: generate an elastic-command interface for presentation of the pool consumption savings and an option for the finalization directive.
E10. The system of example E1 or any other example in this table, where the historical multiplexing characteristic, the predicted multiplexing characteristic, or both include a ratio of peak utilization to average utilization.
E11. A method including: at elastic requisition circuitry configured to execute an elastic requisition stack: at a data input layer of the elastic requisition stack, obtaining historical data including data types, the data types including processor utilization type data, operation rate type data, flush volume type data, or any grouping thereof; at a candidate layer of the elastic requisition stack: identifying multiple candidate databases by: obtaining a historical multiplexing characteristic for each of the multiple candidate databases via a map of the historical data; via a deep-learning analysis of the historical data, obtaining a predicted multiplexing characteristic for each of the multiple candidate databases via a map of predicted activity; identifying a complement factor from among the historical multiplexing characteristics; predicted multiplexing characteristics; or both for the multiple candidate databases, the complement factor consistent with a least one statistical multiplexing efficiency among the multiple candidate databases; and aggregating the multiple candidate databases into a candidate pool based on the complement factor;

TABLE 9-continued

Examples
for each of multiple candidate databases, determining a database-compute tier based on a corresponding activity factor, the corresponding activity factor based on the historical data for the individual one of the multiple candidate databases; and
assigning a candidate pool tier consistent with the database-compute tiers of the multiple candidate databases;
at a pool layer of the elastic requisition stack:
performing a performance score operation on the candidate pool by:
computing a disunion performance score for unpooled operation of the individual ones of the multiple candidate databases;
computing a union performance score for pooled operation of the multiple candidate databases; and
at a time that the union performance score exceeds the disunion performance score, generating a pool prescription token for requisition of the candidate pool including the multiple candidate databases;
at a requisition layer of the elastic requisition stack:
responsive to the pool prescription token, receiving a finalization directive; and
based on the finalization directive, generating a pool requisition token; and
at network interface circuitry, sending the pool requisition token to a host interface for control of database-compute resources.
E12. The method of example E11 or any other example in this table, further including, at the pool layer:
at a time that the union performance score fails to exceed the disunion performance score:
performing a pool revision operation on the candidate pool by:
determining a revised candidate pool by removing a first candidate database of the multiple candidate databases from the candidate pool; and
performing the performance score operation on the revised candidate pool.
E13. The method of example E12 or any other example in this table, further including, at the pool layer:
iteratively performing performance score operations and pool revision operations until:
union performance score exceeds the disunion performance score; or
a current candidate pool includes a single candidate database.
E14. The system of example E12 or any other example in this table, further including, at the pool layer:
determining the first candidate database by identifying a lowest inclusion rank database of the multiple candidate databases.
E15. The method of example E14 or any other example in this table, where the elastic requisition circuitry is further configured to, at the candidate layer:
determining an inclusion rank for each of the multiple candidate databases based on:
the historical multiplexing characteristic for the candidate database;
the predicted multiplexing characteristic for the candidate database;
a complement factor relevant to the candidate database; or
any grouping thereof.
E16. A product including:
machine-readable media other than a transitory signal; and
instructions stored on the machine-readable media, the instructions configured to, when executed, cause a machine to:
at elastic requisition circuitry configured to execute an elastic requisition stack:
at a data input layer of the elastic requisition stack, obtain historical data including data types, the data types including processor utilization type data, operation rate type data, flush volume type data, or any grouping thereof;
at a candidate layer of the elastic requisition stack:
identify multiple candidate databases by:
obtaining a historical multiplexing characteristic for each of the multiple candidate databases via a map of the historical data;
via a deep-learning analysis of the historical data, obtaining a predicted multiplexing characteristic for each of the multiple candidate databases via a map of predicted activity;
identifying a complement factor from among the historical multiplexing characteristics; predicted multiplexing characteristics; or both for the multiple candidate databases, the complement factor consistent with a least one statistical multiplexing efficiency among the multiple candidate databases; and
aggregating the multiple candidate databases into a candidate pool based on the complement factor;
for each of multiple candidate databases, determine a database-compute tier based on a corresponding activity factor, the corresponding activity factor based on the historical data for the individual one of the multiple candidate databases; and
assign a candidate pool tier consistent with the database-compute tiers of the multiple candidate databases;
at a pool layer of the elastic requisition stack:
perform a performance score operation on the candidate pool by:
computing a disunion performance score for unpooled operation of the individual ones of the multiple candidate databases;
computing a union performance score for pooled operation of the multiple candidate databases; and
at a time that the union performance score exceeds the disunion performance score, generating a pool prescription token for requisition of the candidate pool including the multiple candidate databases;
at a requisition layer of the elastic requisition stack:
responsive to the pool prescription token, receive a finalization directive; and
based on the finalization directive, generate a pool requisition token; and
at network interface circuitry, send the pool requisition token to a host interface for control of database-compute resources.
E17. The product of example E16 or any other example in this table, where the instructions are configured to cause the machine to, at a predictive engine layer of the elastic requisition stack:
perform the deep-learning analysis of the historical data to obtain predicted utilization data including the data types; and
determine the map of predicted activity based on the predicted utilization data.
E18. The product of example E17 or any other example in this table, where the instructions are configured to cause the machine to, at the predictive engine layer, perform the deep-learning analysis of the historical data by training a deep learning algorithm using the historical data to obtain predicted utilization data.
E19. The product of example E16 or any other example in this table, where the instructions are configured to cause the machine to, at a consumption savings layer of the elastic requisition stack:
determine a pool consumption savings based on an amount by which the union performance score exceeds the disunion performance score.
E20. The product of example E19 or any other example in this table, where the instructions are configured to cause the machine to, at a presentation layer of the elastic requisition stack:
generate an elastic-command interface for presentation of the pool consumption savings and an option for the finalization directive.

Various implementations have been specifically described. However, many other implementations are also possible.

What is claimed is:

1. A system including:

elastic requisition circuitry configured to execute an elastic requisition stack, the elastic requisition circuitry configured to:

at a data input layer of the elastic requisition stack, obtain historical data including data types, the data types including processor utilization type data, operation rate type data, flush volume type data, or any grouping thereof;

at a candidate layer of the elastic requisition stack:

identify multiple candidate databases by:

obtaining a historical multiplexing characteristic for each of the multiple candidate databases via a map of the historical data;

via a deep-learning analysis of the historical data, obtaining a predicted multiplexing characteristic for each of the multiple candidate databases via a map of predicted activity;

identifying a complement factor from among the historical multiplexing characteristics; predicted multiplexing characteristics; or both for the multiple candidate databases, the complement factor consistent with a least one statistical multiplexing efficiency among the multiple candidate databases; and

aggregating the multiple candidate databases into a candidate pool based on the complement factor;

for each of multiple candidate databases, determine a database-compute tier based on a corresponding activity factor, the corresponding activity factor based on the historical data for the individual one of the multiple candidate databases; and

assign a candidate pool tier consistent with the database-compute tiers of the multiple candidate databases;

at a pool layer of the elastic requisition stack:

perform a performance score operation on the candidate pool by:

computing a disunion performance score for unpooled operation of the individual ones of the multiple candidate databases;

computing a union performance score for pooled operation of the multiple candidate databases; and

at a time that the union performance score exceeds the disunion performance score, generating a pool prescription token for requisition of the candidate pool including the multiple candidate databases;

at a requisition layer of the elastic requisition stack:

responsive to the pool prescription token, receive a finalization directive; and

based on the finalization directive, generate a pool requisition token; and

network interface circuitry configured to send the pool requisition token to a host interface for control of database-compute resources.

2. The system of claim **1**, where the elastic requisition circuitry is further configured to, at the pool layer:

at a time that the union performance score fails to exceed the disunion performance score:

perform a pool revision operation on the candidate pool by: determining a revised candidate pool by removing a first candidate database of the multiple candidate databases from the candidate pool;

perform the performance score operation on the revised candidate pool.

3. The system of claim **2**, where the elastic requisition circuitry is further configured to, at the pool layer:

iteratively perform performance score operations and pool revision operations until:

union performance score exceeds the disunion performance score; or

a current candidate pool includes a single candidate database.

4. The system of claim **2**, where the elastic requisition circuitry is further configured to, at the pool layer:

determine the first candidate database by identifying a lowest inclusion rank database of the multiple candidate databases.

5. The system of claim **4**, where the elastic requisition circuitry is further configured to, at the candidate layer:

determine an inclusion rank for each of the multiple candidate databases based on:

the historical multiplexing characteristic for the candidate database;

the predicted multiplexing characteristic for the candidate database;

a complement factor relevant to the candidate database; or

any grouping thereof.

6. The system of claim **1**, where the elastic requisition circuitry is configured to, at a predictive engine layer of the elastic requisition stack:

perform the deep-learning analysis of the historical data to obtain predicted utilization data including the data types; and

determine the map of predicted activity based on the predicted utilization data.

7. The system of claim **6**, where the elastic requisition circuitry is configured to, at the predictive engine layer, perform the deep-learning analysis of the historical data by training a deep learning algorithm using the historical data to obtain predicted utilization data.

8. The system of claim **1**, where the elastic requisition circuitry is configured to, at a consumption savings layer of the elastic requisition stack:

determine a pool consumption savings based on an amount by which the union performance score exceeds the disunion performance score.

9. The system of claim **8**, where the elastic requisition circuitry is configured to, at a presentation layer of the elastic requisition stack:

generate an elastic-command interface for presentation of the pool consumption savings and an option for the finalization directive.

10. The system of claim **1**, where the historical multiplexing characteristic, the predicted multiplexing characteristic, or both include a ratio of peak utilization to average utilization.

11. A method including:

at elastic requisition circuitry configured to execute an elastic requisition stack:

at a data input layer of the elastic requisition stack, obtaining historical data including data types, the data types including processor utilization type data, operation rate type data, flush volume type data, or any grouping thereof;

at a candidate layer of the elastic requisition stack:

identifying multiple candidate databases by:

obtaining a historical multiplexing characteristic for each of the multiple candidate databases via a map of the historical data;

via a deep-learning analysis of the historical data, obtaining a predicted multiplexing characteristic for each of the multiple candidate databases via a map of predicted activity;

identifying a complement factor from among the historical multiplexing characteristics; predicted multiplexing characteristics; or both for the multiple candidate databases, the complement factor consistent with a least one statistical multiplexing efficiency among the multiple candidate databases; and

aggregating the multiple candidate databases into a candidate pool based on the complement factor;

for each of multiple candidate databases, determining a database-compute tier based on a corresponding activity factor, the corresponding activity factor based on the historical data for the individual one of the multiple candidate databases; and assigning a candidate pool tier consistent with the database-compute tiers of the multiple candidate databases;

at a pool layer of the elastic requisition stack:

performing a performance score operation on the candidate pool by:

computing a disunion performance score for unpooled operation of the individual ones of the multiple candidate databases;

computing a union performance score for pooled operation of the multiple candidate databases; and

at a time that the union performance score exceeds the disunion performance score, generating a pool prescription token for requisition of the candidate pool including the multiple candidate databases;

at a requisition layer of the elastic requisition stack:

responsive to the pool prescription token, receiving a finalization directive; and

based on the finalization directive, generating a pool requisition token; and

at network interface circuitry, sending the pool requisition token to a host interface for control of database-compute resources.

12. The method of claim **11**, further including, at the pool layer:

at a time that the union performance score fails to exceed the disunion performance score:

performing a pool revision operation on the candidate pool by: determining a revised candidate pool by removing a first candidate database of the multiple candidate databases from the candidate pool; and

performing the performance score operation on the revised candidate pool.

13. The method of claim **12**, further including, at the pool layer:

iteratively performing performance score operations and pool revision operations until:

union performance score exceeds the disunion performance score; or

a current candidate pool includes a single candidate database.

14. The system of claim **12**, further including, at the pool layer:

determining the first candidate database by identifying a lowest inclusion rank database of the multiple candidate databases.

15. The method of claim **14**, where the elastic requisition circuitry is further configured to, at the candidate layer:

determining an inclusion rank for each of the multiple candidate databases based on:

the historical multiplexing characteristic for the candidate database;

the predicted multiplexing characteristic for the candidate database;

a complement factor relevant to the candidate database; or

any grouping thereof.

16. A product including:

machine-readable media other than a transitory signal; and

instructions stored on the machine-readable media, the instructions configured to, when executed, cause a machine to:

at elastic requisition circuitry configured to execute an elastic requisition stack:

at a data input layer of the elastic requisition stack, obtain historical data including data types, the data types including processor utilization type data, operation rate type data, flush volume type data, or any grouping thereof;

at a candidate layer of the elastic requisition stack:

identify multiple candidate databases by:

obtaining a historical multiplexing characteristic for each of the multiple candidate databases via a map of the historical data;

via a deep-learning analysis of the historical data, obtaining a predicted multiplexing characteristic for each of the multiple candidate databases via a map of predicted activity;

identifying a complement factor from among the historical multiplexing characteristics; predicted multiplexing characteristics; or both for the multiple candidate databases, the complement factor consistent with a least one statistical multiplexing efficiency among the multiple candidate databases; and

aggregating the multiple candidate databases into a candidate pool based on the complement factor;

for each of multiple candidate databases, determine a database-compute tier based on a corresponding activity factor, the corresponding activity factor based on the historical data for the individual one of the multiple candidate databases; and

assign a candidate pool tier consistent with the database-compute tiers of the multiple candidate databases;

at a pool layer of the elastic requisition stack:

perform a performance score operation on the candidate pool by:

computing a disunion performance score for unpooled operation of the individual ones of the multiple candidate databases;

computing a union performance score for pooled operation of the multiple candidate databases; and

at a time that the union performance score exceeds the disunion performance score, generating a pool prescription token for requisition of the candidate pool including the multiple candidate databases;

at a requisition layer of the elastic requisition stack:

responsive to the pool prescription token, receive a finalization directive; and

based on the finalization directive, generate a pool requisition token; and

at network interface circuitry, send the pool requisition token to a host interface for control of database-compute resources.

17. The product of claim **16**, where the instructions are configured to cause the machine to, at a predictive engine layer of the elastic requisition stack:

perform the deep-learning analysis of the historical data to obtain predicted utilization data including the data types; and

determine the map of predicted activity based on the predicted utilization data.

18. The product of claim **17**, where the instructions are configured to cause the machine to, at the predictive engine layer, perform the deep-learning analysis of the historical data by training a deep learning algorithm using the historical data to obtain predicted utilization data.

19. The product of claim **16**, where the instructions are configured to cause the machine to, at a consumption savings layer of the elastic requisition stack:

determine a pool consumption savings based on an amount by which the union performance score exceeds the disunion performance score.

20. The product of claim **19**, where the instructions are configured to cause the machine to, at a presentation layer of the elastic requisition stack:

generate an elastic-command interface for presentation of the pool consumption savings and an option for the finalization directive.

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